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METHODS

Relating Network-Instantiated Constructs to Psychological Variables Through Network-Derived Metrics: An Exploratory Study

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Psychological researchers increasingly represent psychological constructs as mutual associations between variables using psychometric network models. Although a natural next step would be to study the relations between such network-instantiated constructs and other psychological variables, it is not yet clear how to best summarize a network in a way that allows researchers to model associations. We evaluated the predictive utility of five different network-derived metrics that were either estimated from or informed by individual network models across four intensive longitudinal datasets. These metrics included three “network-structure” variables (density, global strength, and maximum modularity coefficient), two network-informed variables (individuals’ average value of the most frequently central node across time, and their average value of their own most central node across time), and the average sum score of all nodes in the network across time. Our results showed that, for most outcomes, an individual’s average value of the most frequently central node was the best predictor. This work suggests that person-level networks may be used to inform predictive models.

Keywords: psychometric networks; prediction; intensive longitudinal data

1. INTRODUCTION

Psychometric network models are widely used to represent psychological constructs as webs of pairwise associations. Psychometric networks models visualize the mutual associations (termed *edges*) between variables (termed *nodes*). This modeling approach has been used to represent a variety of psychological constructs ranging from intelligence to mental disorders (Borsboom & Cramer, 2013; Van Der Maas et al., 2017). For example, a network representation of negative affect would examine how items that assess negative affect (the nodes in the network) are mutually related, and these mutual relations would be represented by the connections between the nodes (the edges). After representing a single construct as a network, a natural next step in psychological research would be to use the network-instantiated construct to study the predictive and causal relations among psychological variables. For example, one may want to estimate the extent to which negative affect predicts a person's life satisfaction, and so needs to distill the negative affect network into one or more predictor variables. However, unlike other psychometric construct models (e.g., common factor models), psychometric network models do not model a construct as a single variable (whether observed, such as a sum score, or latent, such as a common factor). As such, it is not obvious how to distill a network into a single variable that supports modeling associations between constructs.

This problem of how to model the associations between a construct that is described by a network and other variables is most evident in the context of psychopathology research, where network models are often estimated with the goal of identifying potential targets for intervention that can assist in treatment. However, the aforementioned problem can also be seen in areas such as political attitudes, cognition, and personality (Beck & Jackson, 2017; Blanken et al., 2019; Bos et al., 2017; Dalege et al., 2017; Ferguson & Initiative, 2021; Klipstein et al., 2020; Nissen & Beck, 2024; Siew et al., 2019; Stella, 2022). For example, Siew et al. (2019) examined how the relations between questionnaire items assessing statistics anxiety differed among students with high versus low statistics anxiety, and how these relations offered different targets for reducing such anxiety. Along similar lines, Beck and Jackson (2017) estimated individual networks of personality items for undergraduate students, and examined how structural properties or the complexity of each individual's network was related to future academic performance and life satisfaction.

These represent only two examples of how networks have been used for prediction, and we describe more in the Network Models and Prediction Using Single Group Networks and Network Models and Prediction Using Multiple Group or Individual Networks sections that follow. The majority of these have fit between-person networks, such that a single network is fit to a whole sample of participants, precluding the possibility of individual differences in network features. When everyone in the sample is assumed to have the same network, the only way to achieve a network summary variable that varies across people is to use the estimated group network to identify a key variable or combination of

variables that can stand in for the network construct. We will refer to this type of summary variable as a "network-informed variable". Another approach, which is only possible with multiple estimated networks (e.g., when different groups or individuals have their own estimated network), is to use features of the networks themselves as summary variables. We will refer to this type of summary variable as a "network structure variable". To date, very little work has explored the use of several possible network summary variables for prediction; instead previous work has chosen a single approach to summarizing the network. In the present paper we identify six summary variables (including 2 network-informed variables, 3 network structure variables, and 1 variable outside the network) and use each of them as predictors in four empirical datasets. Each dataset collected intensive longitudinal data on a number of participants, allowing us to fit individual network models and examine the predictive capacity of each index in all four data sets.

1.1 Network Models and Prediction Using Single Group Networks

When estimated in a single sample, psychometric network models typically represent the mutual associations (or edges) between variables (nodes) as partial correlations (Epskamp & Fried, 2018). That is, each edge in the network represents the unique association between that pair of variables, controlling for all other variables in the network.

Network models have been applied in a wide variety of contexts, including psychopathology (Borkulo et al., 2015; Fried et al., 2018, 2016; Schweren et al., 2018), political attitudes Dalege et al. (2017), and personality (Costantini et al., 2019). When such networks are estimated, interpretation typically focuses on examining the structure of the estimated network, such as the strongest edges, the number and content of clusters, the overall density, and the role that specific nodes play in the system (Borsboom et al., 2021; Golino & Epskamp, 2017). However, when estimating networks in a single group at a single timepoint, it must be assumed that the estimated network applies to every individual in the sample, and so any network structure variable, such as density or the number of clusters, must remain constant across individuals as well.

Therefore, a popular approach when networks have been estimated based on between-person associations among variables in single-group data is to simply use the variable that has the highest centrality coefficient (i.e., the *most central node*) for prediction. Centrality coefficients originated in the field of social networks, and are used to identify which nodes are likely to be the most important or influential to the rest of the system based on their connections with other nodes in the network (Bringmann et al., 2019). Therefore, the motivation for using the most central node as a predictor is that, due to its position in the network, changing the value of this node would result in the most effective change to the rest of the network. This reasoning has been termed the "centrality hypothesis" (Lunansky et al., 2022; Spiller et al., 2020). Indeed, changes in the nodes identified as the most

central in the network have been shown to lead to greater change in the overall network structure itself, compared to change in nodes that are less central (Papini et al., 2020; Robinaugh et al., 2016; Rodebaugh et al., 2018; Spiller et al., 2020), but this idea has also been challenged (Bringmann et al., 2019; Ryan et al., 2022). When examining associations between network-instantiated constructs and relevant psychological variables outside the network, there is evidence that more central nodes do tend to have stronger associations with those variables. In the context of eating disorders, the value of the most central node (or a composite formed of the most central nodes) has been related to response to treatment for anorexia nervosa (Brown et al., 2020; Elliott et al., 2020; Hagan et al., 2023), excessive exercise (Levinson & Williams, 2020), level of clinical impairment (Elliott et al., 2020), and depression and body mass index (Olatunji et al., 2018). Similarly, the two most central symptoms in a network of Obsessive-Compulsive Disorder symptoms and beliefs were each related to participants' depression and anxiety scores (Olatunji et al., 2019). High levels of central nodes were also related to later onset of major depressive disorder (Boschloo et al., 2015) and diagnoses of post-traumatic stress disorder (Haag et al., 2017).

Another approach, also focusing on the the influence of single nodes, is to include the outcome variable of interest in the network itself. This is termed "network outcome analysis", and has been used to examine the direct associations between network variables (such as insomnia and energy level) to the onset of major depressive disorder, or between specific risk factors and recidivism (Berg et al., 2020; Blanken et al., 2019). However, this approach only examines the relation between individual nodes (e.g., specific risk factors) and the outcome of interest, and not between the overall construct represented by the network model (e.g., a person's level of risk) and the outcome. Furthermore, this approach increases the risk of network edges being subject to *collider bias*: individual edges in the network are estimated by controlling for all other variables in the network (including the outcome variable), and so the edge that is estimated between two nodes in the network can be biased or spurious since both are presumed to be a common cause of the outcome variable (Ryan et al., 2022; Wysocki et al., 2022).

While using the network structure to identify the most central node is clearly effective, the summary variable that is produced reflects the level of a single network node, rather than any property of the network itself. Thus, this strategy does not allow a researcher to investigate whether the *system* instantiated in a network has predictive properties. Doing so requires variability in network properties across some unit of prediction (i.e., people or groups). Several studies have used individual or multiple-group networks to examine this question.

1.2 Network Models and Prediction Using Multiple Group or Individual Networks

When data contain two or more known groups (e.g., patients and non-patients, recovered and not recovered, experimental and control), researchers can fit network models within each group and com-

pare how network structure variables differ across groups. For example, researchers have compared network density across different patient populations to test the theory that denser symptom networks (i.e., networks with a greater proportion of non-zero edges between different symptoms) have greater potential to spread activation and thus represent greater vulnerability. These studies have found that, indeed, network density is higher in groups of individuals who persisted in a major depression disorder diagnosis after treatment (Borkulo et al., 2015; Lee et al., 2023; Pe et al., 2015).

Along similar lines, researchers have examined differences in network strength between networks estimated from a group of individuals at two occasions (e.g., before and after treatment). Network strength, which is the sum of the absolute value of all edges, complements network density by taking into account the magnitude of the edges. For example, two networks may have the same connections but those connections are of different magnitudes, and this difference results in changes to one node spreading more or less influence throughout the system. Network strength has been found to increase from before to after treatment (Ding et al., 2023; Smith et al., 2019; Zhou et al., 2022).

Finally, in the areas of social and semantic networks, which investigate the associations between individuals and verbal concepts, respectively, researchers have related the degree of separation between clusters within a network to external variables. In the psychometric network literature, there have been many recent developments in categorizing a network's nodes into clusters (Golino et al., 2020). This is especially the case when the network's nodes are variables of different, but overlapping, disorders, different personality traits (e.g., the Big Five), or measures of both positive and negative affect. After estimating the underlying communities, researchers could examine how well-separated the estimated communities are using measures such as modularity or subgroup insularity (Kenett et al., 2016; Sweet & Zheng, 2018). The reasoning behind this metric is that greater separation between communities means that changes in the network are less likely to spread from one community to the next (Christensen & Kenett, 2021; Sweet, 2019). In the semantic and social network literature, measures of how well communities cluster together has differentiated individuals with and without Asperger's syndrome, and have mediated the relation between mathematics coaching and teachers' beliefs about instruction in different schools (Kenett et al., 2016; Sweet, 2019; Sweet & Zheng, 2018).

When intensive longitudinal data (collected over a large number of timepoints) are available for each individual, network models can now be fit to each individual. This allows researchers to examine how the nodes of the network interact with each other *within* an individual across time, and determine how how changes to one node translate to *future* changes in the system. Fitting network models to individuals results in two networks: the temporal network and the contemporaneous network (Epskamp et al., 2018b).

The temporal network represents the dynamic relations between the nodes in the network through the form of a lag-1 vector autoregressive (VAR(1)) model. In a VAR(1) model, each node in the network at time t is predicted by itself and all other nodes at the previous timepoint, $t-1$. The resulting edges

are directed, and represent the degree to which the variable at the previous timepoint predicts the level of a variable at the current timepoint, controlling for all other variables at the previous timepoint.

The contemporaneous network models the variance-covariance matrix of the residuals from the temporal network as a partial correlation network. The relations between nodes in a contemporaneous network are partial correlations between the residuals of those nodes, after the temporal effects have been taken into account. While the edges in the temporal network are interpreted as relations across time, the edges in a contemporaneous network are interpreted as unique pairwise relations that arose within a single measurement window.

As was the case when fitting network models to multiple groups, both network structure variables and network-informed variables can now vary across individuals, and thus be used for prediction. Levinson et al. (2021) identified which nodes were most often central in temporal and contemporaneous symptom networks across all individuals, and linked the values of these network-informed variables to later severity of individuals' eating disorder. Furthermore, Beck and Jackson (2017) showed that network-structure variables, such as network density and the average clustering coefficient, predicted students' academic success, but not life satisfaction.

1.3 Purpose of the Study

We aim to expand on previous work by systematically exploring the predictive ability of a number of network-informed and network structure variables across four datasets. These datasets span three areas of psychological research, allowing us to also explore whether there is any consistency with which network characteristic(s) (if any) are most predictive. To answer this question, we estimated temporal networks[1] for each individual in each dataset, extracted six different summary characteristics, and used those to predict relevant outcomes.

2. METHODS

2.1 Datasets

To maximize the generalizability of our results, we chose four datasets that focused on three different research areas: romantic relationships (Ferrer et al., 2012), personality (Beck & Jackson, 2017), and affect (Dejonckheere et al., 2019; Koval et al., 2013). Descriptions of each dataset are given in the following sections, and demographic information is summarized in Table 1.

[1] Results from when the summary characteristics were extracted from the contemporaneous network instead are available at https://osf.io/esh2y/

2.1.1 Dynamics in Dyadic Interactions Project

The Dynamics in Dyadic Interactions Project (DDIP) was a longitudinal study that examined the emotional dynamics of romantic couples over time (Ferrer et al., 2012). As part of the study, 282 heterosexual couples completed a daily diary questionnaire for up to 90 days, answering questions related to their overall affect and affect specific to their relationship. On average, participants completed 53.9 timepoints ($SD = 22.4$).

To measure affect towards their relationship, each member of the couple completed the Relationship-Specific Affect questionnaire. This questionnaire contained 18 items designed to measure both positive (9 items) and negative (9 items) affect. Participants were asked to “Indicate to what extent you have felt this way about your relationship today”, and responded using a Likert-type scale ranging from 1 (*very slightly or not at all*) to 5 (*extremely*). Each dyad’s network was formed from both members’ responses, resulting in a total of 36 nodes.

One and two years after the daily diary study, participants participated in follow-up interviews. During these interviews, they were asked about their current relationship status, and those no longer together with their initial partner at either interview were recorded as having ended their relationship. Additionally, participants’ relationship quality was assessed using six items from the Perceived Relationship Quality Component Inventory (Fletcher et al., 2000). Participants responded to items such as “How satisfied are you with your relationship?” and “How committed are you to your relationship?” using a Likert-type scale that ranged from 1 (*not at all*) to 7 (*extremely*). An overall relationship quality score was formed by averaging the responses of both members of the couple. Thus, the two outcome measures of interest for our regression analyses were whether or not couples had ended their relationship, and their relationship quality. Full details of the study procedures and all measures can be found at Ferrer et al. (2012).

2.1.2 Personality and Interpersonal Roles Study

As part of the Personality and Interpersonal Roles Study (PAIRS; Vazire et al., 2015), 345 undergraduate students (235 female) at Washington University in St. Louis completed experience sampling method (ESM) surveys across two waves of data collection. For this study, we use only the first wave of data collection. Five participants were excluded for not having provided information on the outcome variables of interest.

As part of the ESM survey, participants received four emails per day for two weeks with links to the ESM survey. In each survey, participants responded to questions about their situation (e.g., ”During the past hour, were you interacting with other people?”), emotions (e.g., ”Did you keep your emotions to yourself?”), and behavior (e.g., ”During the past hour, did you study or work?”) in the last hour.

There were also nine personality items related to the domains of agreeableness, conscientiousness, extraversion, and neuroticism taken from the BFI-44 (John, 1991), but which were modified to reflect the collection periods of the ESM survey (e.g., "From 5-6 PM, how 'considerate or kind' were you?"). All questions were answered using a Likert-type scale that ranged from 1 (*Not a lot*) to 5 (*Very*). For items related to agreeableness, missing data was imputed using the average value of that item across all timepoints, as these items were only asked if participants reported having interacted with someone in the previous hour. Out of all the surveys participants completed, they responded to, on average, 82.8% of all agreeableness items ($SD = 15.4$%). Items related to rudeness, quietness, laziness, and relaxation were reverse coded. On average, participants completed 32.4 ($SD = 13.8$) of the 56 surveys. These nine personality items formed the nodes of each individual's network.

At the start of the ESM survey, participants were also asked to report their current college GPA, which ranges from 1.0 to 4.0, and life satisfaction, which was answered using a Likert-type scale ranging from 1 (*Completely dissatisfied*) to 15 (*Completely satisfied*). These two variables were chosen as the outcomes of interest for this study, due to their reported and reliable associations with personality factors (Beck & Jackson, 2017). Full details of the study procedures and all measures can be found at Vazire et al. (2015).

2.1.3 Koval et al. (2013)

As part of a larger study on emotional functioning, Koval et al. (2013) collected ESM data[2] on 100 undergraduates (62 female) at KU Leuven. We hereafter refer to this dataset as KPMK. Four participants were excluded from the dataset due to equipment malfunction or poor ESM compliance, and one withdrew from the study, leaving a total of 95 participants.

As part of the ESM portion of the study, participants were prompted 10 times a day for seven days to respond to the survey assessing their current positive and negative affect. The survey contained two items related to positive affect (*happy* and *relaxed*) and five items related to negative affect (*sad*, *depressed*, *anxious*, *stressed*, and *angry*). Participants responded using a slider that ranged from 1 (*not at all*) to 100 (*very much*). These seven affect items formed the nodes of each individual's network.

Prior to the ESM portion of the study, participants completed two questionnaires to assess depressive symptoms and life satisfaction. The frequency of participants' depressive symptoms over the past week were assessed using the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977). The CES-D contains 20 items that are answered on a scale of 0 (*rarely or none of the time*) to 3 (*most or all of the time*). Furthermore, participants completed the Satisfaction with Life scale (SWL; Diener et al., 1985) to assess their overall life satisfaction. This questionnaire contains five items on which participants respond on a scale of 1 (*strongly disagree*) to 7 (*strongly agree*). In our regression analyses, participants' depression scores (measured as the average score of all items in the CES-D)

and life satisfaction scores (measured as the average score of all items in the SWL) were our outcomes of interest. Full details of the study procedures and all measures can be found at Koval et al. (2013).

2.1.4 Dejonckheere et al. (2019)

Dejonckheere et al. (2019) collected data[2] on 100 community members (77 female), which we hereafter refer to as the DKPK dataset. As part of an ESM survey, participants were prompted seven times a day for two weeks to report on their current affect. The affect items asked about both positive affect (how happy and how relaxed participants were at that moment) and negative affect (how sad, angry, and stressed participants were at that moment). Participants responded using a slider that ranged from 0 (*not at all*) to 100 (*very much*). These five affect items formed the nodes of each individual's network.

Prior to starting the ESM survey, participants also completed three questionnaires: two related to depressive symptoms (the CES-D and the Beck Depression Inventory-II BDI-II; Beck et al., 1987), and one related to life satisfaction (the SWL). Unlike the CES-D, which assesses the frequency of depressive symptoms over the past week, the BDI-II assesses the *intensity* of 20 depression symptoms over the past week, and is answered on a scale of 0 (*absent*) to 3 (*very severe*). For each questionnaire, the average scores across all items were used as the outcomes of interest. Full details of the study procedures and all measures can be found at Dejonckheere et al. (2019).

Table 1
Demographic information for each dataset

	DDIP	PAIRS	KPMK	DKPK
Sample Size[a]	282	345	95	100
# Female Participants	282	235	62	77
Study Type	Daily Diary	ESM	ESM	ESM
Occasions per Day	1	4	10	7
Number of Days	90	14	7	14
Total Possible T	90	56	70	98
Average Completed Timepoints (SD)	53.9 (22.4)	32.4 (13.8)	60.2 (4.60)	87.0 (9.38)
Network Variables	Relationship Affect	Personality	Affect	Affect

[a] In the DDIP dataset, sample size refers to the number of heterosexual couples. In the PAIRS, DKPK, and KPMK datasets, sample size refers to the number of individuals.

2.2 Network Estimation and Summary Statistics

We estimated individual temporal and contemporaneous networks for each individual (or, in the case of the DDIP dataset, each dyad). Networks were estimated using a non-regularized estimation approach, based on research suggesting that non-regularized approaches to network estimation are more consistent and result in more accurate estimation of non-zero edges than regularized estimation approaches (Williams & Rast, 2020; Williams et al., 2019). In this approach, VAR(1) models were fit for each node, and non-significant edges were pruned from the network based on a significance level of

[2]These datasets can be found at https://osf.io/zm6uw/

.05. The model was refit, and the process was repeated until no more edges could be removed. This estimation was carried out using the var1 function in the psychonetrics package (Epskamp, 2023).

From each individual's temporal network, we then extracted each of the following summary statistics: the network density, the network strength, two summary statistics based on centrality indices (the average value of each individual's central node, and the average value of the most commonly central node), how well-separated underlying communities in the network were, and an unweighted sum score. In order to illustrate the summary statistics and their interpretation, we shall use a hypothetical example of a network that is formed of six negative affect items: nervous, irritable, ashamed, hostile, distressed, and upset. All code is available at https://osf.io/esh2y/.

2.2.1 Network Density

One straightforward way to measure how easily influence can spread throughout a network is to calculate network density, or the proportion of non-zero edges out of all possible edges. If w_{jk} represents the weight of the edge pointing from node j to node k, then the network density is calculated as:

$$\frac{\mathbb{1}_{w_{jk}\neq 0}}{\frac{p(p+1)}{2}},$$

where p is the total number of nodes in the network, and $\mathbb{1}_{w_{jk}\neq 0}$ is an indicator function that equals 1 if the edge between node j and node k is non-zero.

Networks with higher density have more connections present between nodes, and so a change to one node in the network is more likely to affect nodes in the rest of the network. This can be likened to a domino effect - if one domino falls (or one node in the network is changed), then many other dominoes are likely to fall due to their proximity or connection to the first node. As more and more nodes are affected, this can cause the system represented by the network to tip into a worse state (which is in line with the vulnerability hypothesis; Cramer et al. 2016; Schweren et al. 2018) or a more protective state (Schueler et al., 2021), depending on the nature of the exact nodes in the network (e.g., clinical symptoms versus items related to a person's resilience).

In our example of a network of negative affect, greater density indicates more connections between nodes, so that a person who feels nervous is also more likely to feel ashamed and irritable over time, increasing their overall feelings of negative affect. On the other hand, a negative affect network with lower density could indicate that a person might feel nervous, but that is unlikely to correspond with changes in how ashamed or irritable they feel at the next timepoint.

2.2.2 Network Strength

Our second measure, global network strength, is the sum of the absolute value of all edges in the network (Borkulo et al., 2022). The network strength, S, is calculated as:

$$S = \sum_{k=1}^{p} \sum_{j=1}^{p} |w_{jk}|.$$

Network strength provides an important complement to network density, by taking not only the presence or absence of edges into account, but also the value of those edges. Network strength is higher when the network is more densely connected (due to the presence of more edges), but also when those edges are of greater magnitude. Returning to the domino example, networks with greater strength are similar to dominoes that are placed very close together (compared to networks with weaker connections, where the dominoes are spread further apart). Therefore, when the connections in the network are stronger, a change in one node is much more likely to affect the nodes it is connected to (or to tip the other dominoes; Cramer et al. 2016).

In our negative affect example, we could imagine two individuals who have networks of negative affect with the same density. However, in one individual, the connections between nodes are much weaker (i.e., strength is low): therefore, although a change in how nervous a person is feeling is likely to affect how irritable or ashamed they feel at the next timepoint (due to the presence of a connection between those nodes), the smaller magnitude of those connections means that the overall change in their level of irritability or shame is likely to be small. On the other hand, when the connections between the nodes are stronger, how nervous the person is more strongly affects their level of irritability and shame, once again resulting in higher feelings of negative affect over time.

2.2.3 Modularity

To obtain an estimate of how well-separated or insular the underlying communities were in our datasets, we first conducted a Dynamic Exploratory Graph Analysis (DynEGA) upon each individual's time series, using the dynEGA function from the EGAnet package (Golino & Christensen, 2023). Unlike the temporal networks previously described, in which the nodes represent the value of each variable and edges between nodes represent how the value of a variable at one timepoint is related to the value of another variable at the next timepoint, DynEGA estimates a network in which the nodes represent the amount of change in that variable over time, and edges represent the connection between the change in one variable and the change in another variable. DynEGA then applies a community detection algorithm to this estimated network, so that nodes in the same community show similar patterns of change over time (Golino et al., 2022).

The *maximum modularity coefficient* is a measure of how dense the networks within a community are and how sparse the connections are between nodes of different communities (Fortunato, 2010; Newman, 2006). Modularity values closer to the maximum of 1 indicate more well-separated networks, or networks whose nodes have many connections to other nodes in their own community, but very few connections to nodes outside their community (Siew, 2013). The maximum modularity coefficient, Q, is calculated as:

$$Q = \frac{1}{2S} \sum_{j=1}^{p} \sum_{k=1}^{p} \left[w_{jk} - \frac{d_j d_k}{2S} \right] \delta(c_j, c_k),$$

where S is the network strength as calculated in the previous section, w_{jk} is the weighted edge between node j and node k, d_j represents the sum of all edges connected to node j, and $\delta(c_j, c_k)$ is 1 if nodes j and k are in the same community and 0 otherwise.

As mentioned in the Introduction, network modularity as calculated from psychometric networks has not been commonly used as a predictor, although it has been used in both semantic and social networks (Christensen & Kenett, 2021; Sweet, 2019). However, the reasoning of using modularity as a predictor follows along the same lines as network density or network strength - the more modular a network is, the more separated the communities in the network are. Therefore, a change to one node would mainly affect the other nodes in its community, and would not have a large effect on nodes in other communities, limiting the spread of influence throughout the network. In our domino example, this would be as if there were groups of dominoes clustered together, and the maximum modularity coefficient represents how close or far those clusters were to each other. If the maximum modularity coefficient was high, the clusters of dominoes are farther apart, so tipping a domino over in one cluster is unlikely to tip over dominoes in a different cluster.

Suppose our hypothetical network of negative affect had one community between the variables *nervous*, *irritable*, and *ashamed*, and another community formed of the variables *hostile*, *upset*, and *distressed*. This indicates that each of the variables in these communities change in a similar fashion over time. Greater modularity between these communities would indicate that changes in how irritable an individual feels will likely result in changes to how ashamed or nervous they feel, but will not necessarily change how hostile, distressed, or upset they feel. Once again, this would lead to fewer changes in a person's overall negative affect.

We estimated the maximum modularity coefficient of each individual's community structure using the modularity function in EGAnet.

2.2.4 Value of Most Central Node Based on Out-Strength

As described in the Introduction, one of the most commonly used network metrics for prediction is the value of the most central node(s). Although there are numerous centrality indices available (such as betweenness, closeness, expected influence, or controllability centrality), we will use strength centrality. In an undirected network, the strength centrality of a node is the sum of the absolute value of all edges connected to that node (Epskamp et al., 2018a). Due to variables with high strength centrality having more and/or stronger connections, these variables are thought to be the most influential in the system, such that changing its value would be the most effective way to change the values of the other variables (Lunansky et al., 2022). In addition, strength centrality is considered the most stable of the centrality indices (Epskamp et al., 2018a; Lunansky et al., 2022; Rodebaugh et al., 2018).

Since we are estimating temporal networks, containing directed edges, we focused on out-strength centrality. The out-strength centrality for node j is calculated as:

$$\sum_{k \neq j} |w_{jk}|,$$

or the sum of the absolute value of edges directed away from the node. A node with high out-strength centrality would have the most potential to affect other variables in the network through direct effects on other variables, as well as through downstream effects.

We estimated out-strength centrality for each variable in an individual's temporal network, and identified which variable had the highest out-strength centrality, which we call MC_i. We then calculated the individual's average score on their most central variable across all measurement occasions:

$$\bar{X}_{MC_i} = \frac{1}{T} \sum_{t=1}^{T} X_{it,p=MC_i},$$

where X_{itp} represents the value of node p at time t for person i. Although this summary variable is an average value across different nodes, it allows us to somewhat approximate the situation where researchers want to implement personalized interventions for an individual.

In order to have a second measure that was consistent across the individuals in our sample, we also identified which variable was most frequently identified as the one with the highest out-strength centrality, which we call MC_g. We then calculated the average value of this commonly central node across all measurement occasions for each individual:

$$\bar{X}_{MC_g} = \frac{1}{T} \sum_{t=1}^{T} X_{it,p=MC_g}.$$

Therefore, we had two measures based on node centrality to use in our prediction: one for the average

value across time of the individual's most central node, and one for the average value across time of the most frequently central node.

For our example, suppose *hostile* was identified as the node with highest out-strength centrality for an individual. This would mean that a change to how hostile a person feels is more likely to result in changes to other feelings of negative affect than a change to a different variable, such as *guilt*. With our individualized measure of centrality, $\bar{X}_{MC_i}$, we would be interested in how this person's average level of hostility relates to an outcome, since we think hostility is the most representative for how much negative affect this individual experiences. We might also examine how the overall level of the *upset* variable relates to the outcome, even though it was not the most influential node for this individual, but because it was the most influential for a majority of participants in the sample.

Out-strength centrality was calculated using the centralityTable function in qgraph (Epskamp et al., 2012).

2.2.5 Sum Scores

Finally, to provide a point of comparison to the above network characteristics, we also estimated an unweighted sum score from all variables for each individual. The sum score is the simplest way to summarize multiple variables that measure a construct, and allows us to determine whether estimating a temporal network provides more information than a simple composite. Therefore, we calculated the average sum score for each participant across all measurement occasions:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{p=1}^{P} X_{itp}.$$

The sum score of a set of variables is typically a good representation of the overall level of the underlying construct. For example, in our negative affect network, a higher sum score would indicate high levels of negative affect over the course of the study. However, sum scores do not take into account the interactions between variables across time, so including the sum score in our comparisons allows us to examine whether taking such dynamics into account provides additional information that is useful for prediction.

In summary, we were interested in the predictive utility of six different network characteristics: the density of the individual's temporal network, the strength of the temporal network, the modularity of the network, the average value over time of the variable most frequently identified as having the highest out-strength across participants, the average value over time of the variable with the highest out-strength for each individual, and the unweighted sum score of all variables averaged over time.

2.3 Relation to Outcomes

To examine relations between each of the 5 network-derived summary variables and the average sum score to the outcome variables in each dataset, each characteristic was entered into separate simple regression models estimated using ordinary least squares, with each outcome as the dependent variable. Next, to assess whether any of these measures were still able to uniquely predict the outcome after controlling for all other measures, we entered all variables simultaneously into a multiple regression model. The multiple regression analyses were conducted in lavaan, in order to use full-information maximum likelihoood estimation to deal with missing data (Rosseel, 2012). We assessed the predictive ability of each summary variable based on statistical significance; to avoid capitalizing on chance we used a false discovery rate adjustment across all p-values related to a specific network feature. We also examined the adjusted R^2 of the model, or in the case of the multiple regression models, the squared semi-partial correlation, to examine how much (unique) variance is explained by each metric.

3. RESULTS

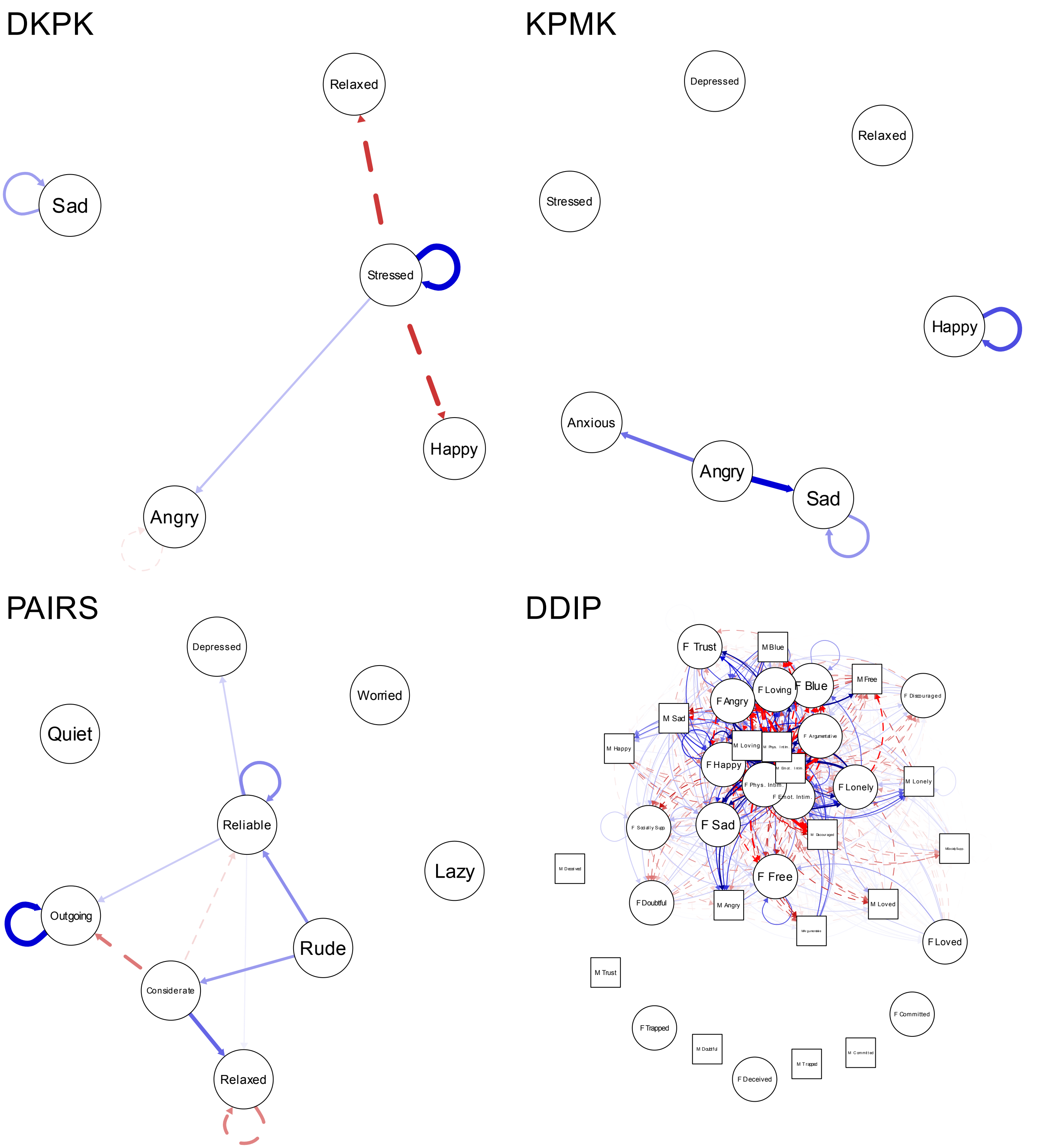
3.1 Model Convergence

Estimation of the temporal networks failed to converge for 5 participants in the PAIRS dataset, and 163 participants in the DDIP dataset. This resulted in a total of 100 converged models for individuals in the DKPK dataset, 95 converged models for individuals in the KPMK dataset, 335 converged models for individuals in the PAIRS dataset, and 119 converged models for couples in the DDIP dataset. Examples of estimated temporal networks from a single individual (or dyad) are plotted in Figure 1.

Even when the estimation of a network for an individual may have been successful, it was possible for that individual to still be missing data for some network features. The reasons for missing values on the metrics varied. For example, some participants had networks with no estimated edges. Although this would provide a valid value for network density (a value of 0), this would prevent out-strength centrality from being calculated (due to the absence of any edges). Thus, a participant with an estimated empty network would be missing a response to the average value of their own most central node. For similar reasons, participants whose networks only had autoregressive effects (where the value of a node at a previous timepoint predicts itself at the next timepoint) would not have values of out-strength centrality, and therefore would be missing a response for the average value of their most central node. However, due to the aggregation of information across participants, they would have a response for the average value of the most frequently central node. Some metrics, such as the average value of the most frequently central node or the average sum score, were never missing, due to the aggregation of information across participants who did have nodes with out-going arrows or the lack of reliance on an estimated network.

Figure 1

Estimated Temporal Networks from Each Dataset



Note. Blue solid lines between nodes represent positive lag-1 relations, while red dashed lines represent negative lag-1 relations. The example network for the DDIP dataset displays nodes related to the female member's scores as circles, and nodes related to the male member's scores as squares.

Table 2
Summary Statistics for Network Features and Community Structure

	DKPK	KPMK	PAIRS	DDIP
Density	0.17 (0.29)	0.31 (0.43)	0.65 (0.46)	0.74 (0.43)
Number of Communities	1.35 (0.48)	1.84 (0.67)	2.49 (0.71)	4.96 (1.48)
Modularity	0.18 (0.18)	0.29 (0.12)	0.28 (0.13)	0.39 (0.10)
Most Commonly Central Node	62.65 (11.87)	25.69 (15.08)	4.54 (0.37)	2.74 (0.79)
Individual's Central Node	37.73 (27.11)	26.28 (22.56)	3.08 (1.11)	2.40 (1.09)
Network Strength	1.90 (5.70)	4.30 (8.28)	5.87 (7.84)	29.05 (24.66)
Sum Score	152.95 (24.03)	183.44 (42.65)	27.27 (1.99)	84.63 (13.06)

Note. Number of communities = number of communities identified by the community detection algorithm. Modularity = Maximum modularity coefficient, Network strength = global network out-strength.

Table 2 presents summary statistics for the six network metrics we examined, as well as the number of estimated communities, for each dataset, averaged across participants. We have also provided correlation matrices among the six network metrics in Table 5. Networks estimated from the PAIRS and DDIP datasets appeared to be more interconnected than those estimated from the DKPK and KPMK datasets, although as can be seen in Figure 2, there was great variability in the density of the estimated networks. Most networks, especially for the PAIRS and DDIP datasets, were either empty (density value of 0) or fully saturated (density value of 1). The average number of estimated communities was between 1 and 2 in the DKPK and KPMK datasets, between 2 and 3 for the PAIRS dataset, and close to 5 for the DDIP dataset. The estimated communities appeared relatively well integrated, as the maximum modularity coefficient was rather low (less than 0.5) for all datasets.

3.2 Prediction Results

Regression results for all metrics are available in Tables 3 and 4, and are plotted in Figures 3 and 4. Regression coefficients are standardized to represent correlation coefficients, which allows us to discuss the association between the network features and our outcomes, even though some outcomes were measured before the ESM portion of the study that was used to estimate the temporal networks.

When each predictor was individually entered into a simple regression model, no network-structure variables (network density, network strength, or the maximum modularity coefficient) were significant predictors of any outcome. Instead, the most consistently significant predictor was a network-informed variable: the average value of the node that was most frequently central across all individuals' networks. This network-derived metric was a statistically significant predictor in seven out of the nine outcomes assessed. Specifically, participants who felt happier had lower depression scores ($\beta_{CESD} = -0.43$, $p < .001$ and $\beta_{BDI} = -0.34$, $p = .001$) and higher life satisfaction ($\beta = 0.43$, $p < .001$) in the DKPK dataset; participants who felt more stressed had higher depression scores ($\beta = 0.47$, $p < .001$) and lower life satisfaction ($\beta = -0.47$, $p < .001$) in the KPMK dataset; participants who felt less lazy had higher life satisfaction ($\beta = 0.13$, $p = .02$) in the PAIRS dataset; and dyads where the male partners felt more

Figure 2
Histograms of the Density of Estimated Temporal Networks for Each Dataset

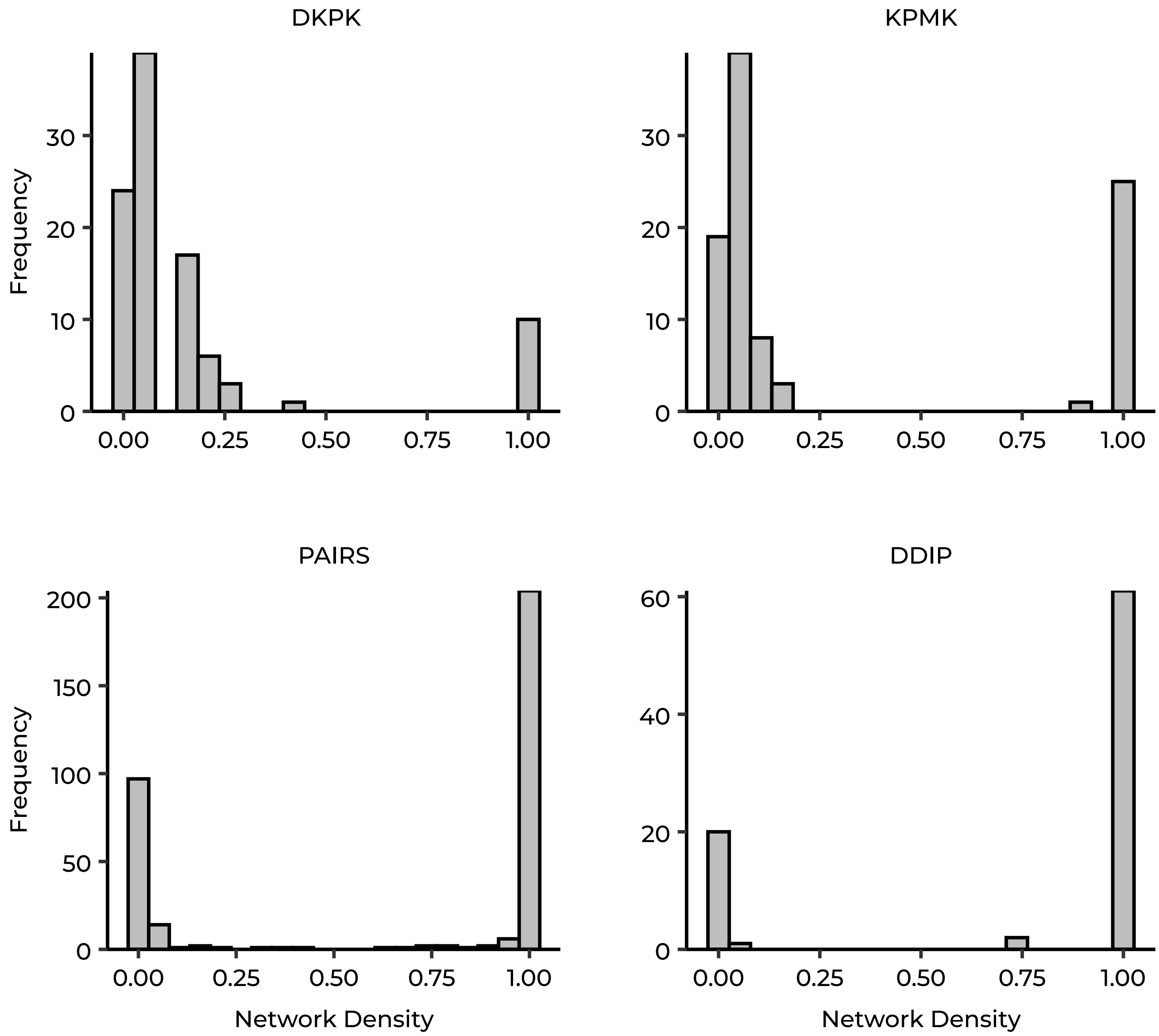
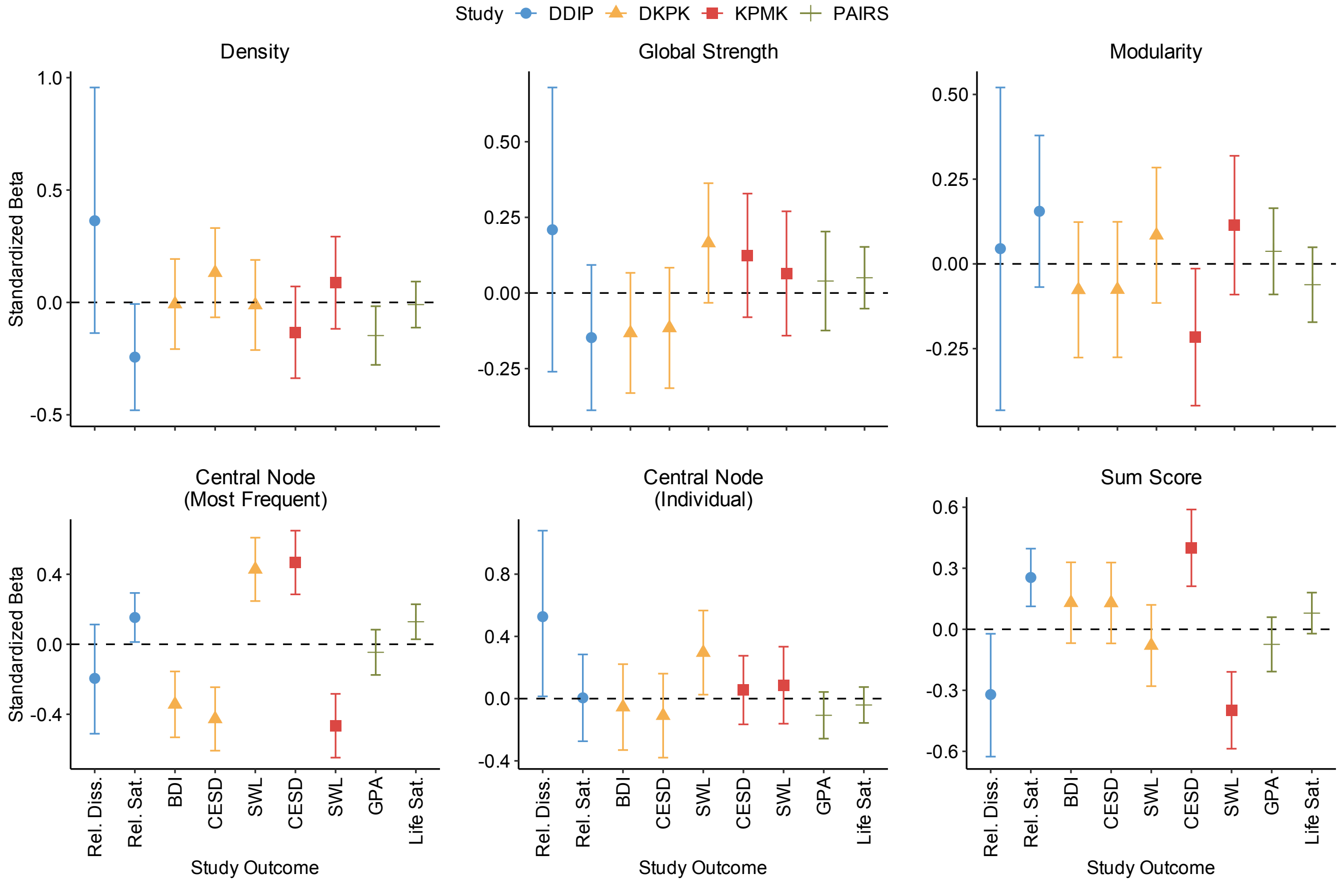


Figure 3

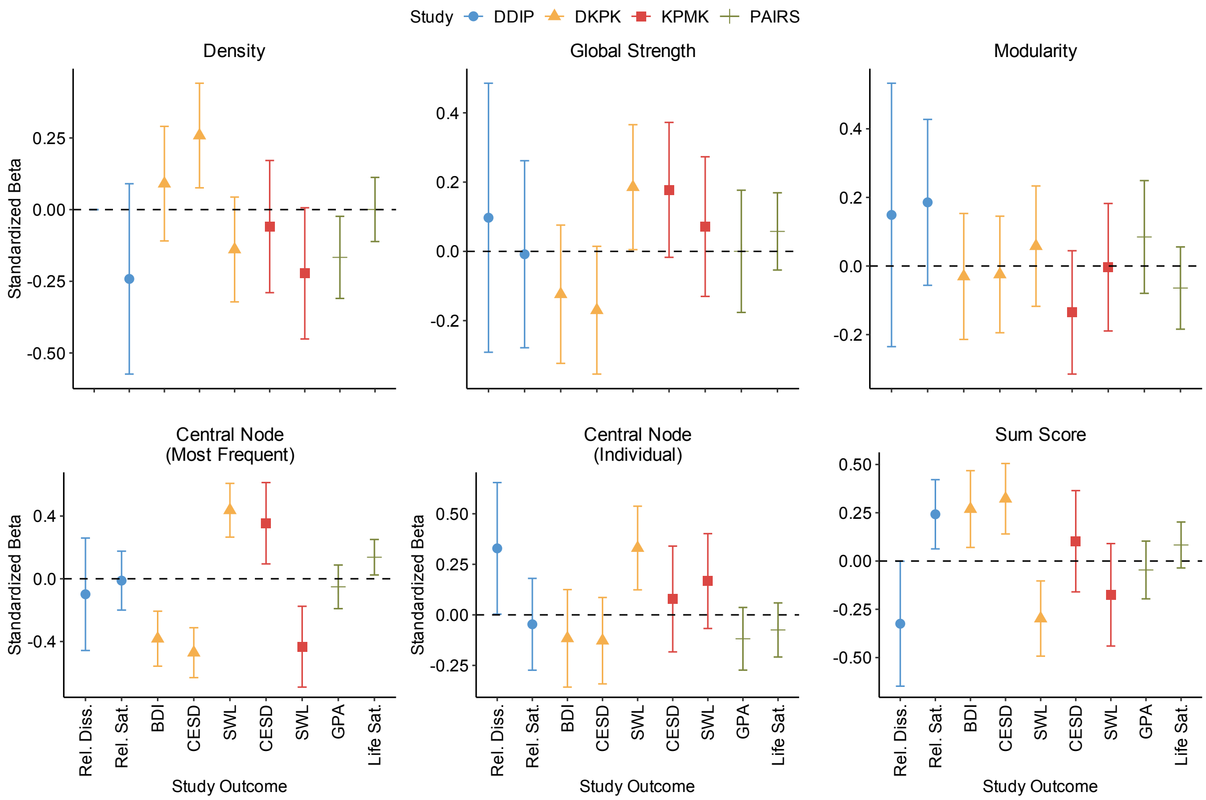
Simple regression results for all summary variables



Note. This plot displays standardized beta estimates from when each summary variable was individually used to predict the outcome. Each plot is a different feature, and outcomes are on the x-axis (Rel. Diss = Relationship Dissolution, Rel. Sat. = Relationship Satisfaction, CESD = average score on Center for Epidemiologic Studies Depression Scale, BDI = average score on Beck Depression Inventory, SWL = average score on Satisfaction with Life Scale, Life Sat. = Life Satisfaction). Bars represent 95% confidence intervals.

Figure 4

Multiple regression results for all summary variables



Note. This plot displays standardized beta estimates from when all summary variables were used to predict the outcome in a multiple regression model. Each plot is a different feature, and outcomes are on the x-axis (Rel. Diss = Relationship Dissolution, Rel. Sat. = Relationship Satisfaction, CESD = average score on Center for Epidemiologic Studies Depression Scale, BDI = average score on Beck Depression Inventory, SWL = average score on Satisfaction with Life Scale, Life Sat. = Life Satisfaction). Bars represent 95% confidence intervals. Due to issues with model estimation, no estimate is available for when density is used to predict relationship dissolution.

physically intimate towards the relationship had higher relationship satisfaction ($\beta = 0.15$, $p = .05$) in the DDIP dataset.

The only other predictor that was significant in the simple regression models was the average sum score, which does not rely on estimation of the temporal network. The average sum score was a significant predictor of greater depression ($\beta = 0.40$, $p < .001$) and lower life satisfaction ($\beta = -0.40$, $p < .001$) in the KPMK dataset. In the DDIP dataset, the average sum score was a significant predictor of higher relationship satisfaction ($\beta = 0.25$, $p = .002$).

When all network features were entered into a multiple regression model, network-structure variables continued to be unrelated to any outcome in all datasets. The average value of the most frequently central node remained a significant predictor of all outcomes in the DKPK and KPMK datasets, and of life satisfaction in the PAIRS dataset, above and beyond all other network features. In addition, when controlling for all other network-derived metrics, the average value of an individual's most central node now predicted life satisfaction in the DKPK dataset. Finally, the average sum score of affect items continued to predict relationship satisfaction in the DDIP dataset. However, although it no longer predicted depression and life satisfaction in the KPMK dataset, it *was* a significant predictor of depression and life satisfaction in the DKPK dataset.

Table 3
Regression results for network structure variables

Predictor	Outcome	Simple Regression					Multiple Regression				
		Estimate	SE	t	p-value	R^2	Estimate	SE	t	p-value	R^2
Density	DDIP - Rel. Diss	0.36	0.27	1.33	.34	.03	-	-	-	-	-
	DDIP - Rel. Sat.	-0.24	0.12	-2.05	.19	.04	-0.24	0.17	-1.43	.34	.03
	DKPK - BDI	-0.01	0.10	-0.07	.99	-.01	0.09	0.10	0.89	.56	.01
	DKPK - CESD	0.13	0.10	1.32	.34	.01	0.26	0.09	2.78	.09	.05
	DKPK - SWL	-0.01	0.10	-0.11	.99	-.01	-0.14	0.09	-1.49	.34	.02
	KPMK - CESD	-0.13	0.10	-1.29	.34	.01	-0.06	0.12	-0.50	.80	-.01
	KPMK - SWL	0.09	0.10	0.85	.56	-.003	-0.22	0.12	-1.90	.19	.03
	PAIRS - GPA	-0.15	0.07	-2.23	.15	.02	-0.17	0.07	-2.28	.15	.02
	PAIRS - Life Sat.	-0.01	0.05	-0.19	.99	-.003	0.00	0.06	0.01	.99	.00
Network Strength	DDIP - Rel. Diss	0.21	0.24	0.88	.57	.01	0.10	0.20	0.49	.71	.01
	DDIP - Rel. Sat.	-0.15	0.12	-1.22	.50	.01	-0.01	0.14	-0.06	1.00	.00
	DKPK - BDI	-0.13	0.10	-1.32	.50	.01	-0.12	0.10	-1.22	.44	.01
	DKPK - CESD	-0.12	0.10	-1.15	.50	.003	-0.17	0.09	-1.80	.50	.03
	DKPK - SWL	0.16	0.10	1.66	.45	.02	0.19	0.09	2.01	.44	.03
	KPMK - CESD	0.12	0.10	1.21	.50	.005	0.18	0.10	1.79	.44	.03
	KPMK - SWL	0.06	0.10	0.62	.69	-.007	0.07	0.10	0.70	.67	.004
	PAIRS - GPA	0.04	0.08	0.48	.71	-.004	0.00	0.09	0.00	1.00	.001
	PAIRS - Life Sat.	0.05	0.05	0.97	.54	-.00	0.06	0.06	1.01	.54	.003
Modularity	DDIP - Rel. Diss	0.05	0.24	0.19	.90	.001	0.15	0.20	0.76	.68	-.05
	DDIP - Rel. Sat.	0.16	0.11	1.38	.68	.01	0.19	0.12	1.50	.68	.03
	DKPK - BDI	-0.08	0.10	-0.76	.68	-.004	-0.03	0.09	-0.32	.87	.002
	DKPK - CESD	-0.08	0.10	-0.75	.68	-.004	-0.02	0.09	-0.28	.87	.00
	DKPK - SWL	0.08	0.10	0.83	.68	-.003	0.06	0.09	0.65	.72	.003
	KPMK - CESD	-0.22	0.10	-2.12	.66	.04	-0.14	0.09	-1.47	.68	.02
	KPMK - SWL	0.11	0.10	1.11	.68	.002	-.002	0.09	-0.04	.97	-.002
	PAIRS - GPA	0.04	0.06	0.56	.73	-.004	0.08	0.08	1.01	.68	.01
	PAIRS - Life Sat.	-0.06	0.06	-1.09	.68	.001	-0.06	0.06	-1.05	.68	.004

Note. Bolded lines represent effects that are significant after a false discovery rate adjustment. Rel. Diss. = Relationship Dissolution, Rel. Sat. = Relationship Satisfaction, CESD = Center for Epidemiologic Studies Depression Scale, BDI = Beck Depression Inventory, SWL = Satisfaction with Life Scale, Life Sat. = Life Satisafaction, Modularity = Maximum modularity coefficient, Network strength = global network out-strength. R^2 for multiple regression analyses is the squared semi-partial correlation.

Table 4
Regression results for network-informed variables and average sum score

		Simple Regression					Multiple Regression				
Predictor	Outcome	Estimate	SE	t	p-value	R^2	Estimate	SE	t	p-value	R^2
Central Node	DDIP - Rel. Diss	-0.19	0.16	-1.23	.28	0.01	-0.10	0.18 -0.54	.62	.01	
(Most Frequent)	DDIP - Rel. Sat.	**0.15**	**0.07**	**2.15**	**.05**	**.02**	-0.01	0.10	-0.12	.90	.01
	DKPK - BDI	**-0.34**	**0.09**	**-3.62**	**.001**	**.11**	**-0.38**	**0.09**	**-4.27**	**< .001**	**.13**
	DKPK - CESD	**-0.43**	**0.09**	**-4.67**	**< .001**	**.17**	**-0.47**	**0.08**	**-5.81**	**< .001**	**.20**
	DKPK - SWL	**0.43**	**0.09**	**4.69**	**< .001**	**.17**	**0.44**	**0.09**	**5.00**	**< .001**	**.17**
	KPMK - CESD	**0.47**	**0.09**	**5.10**	**< .001**	**.21**	**0.35**	**0.13**	**2.68**	**.01**	**.06**
	KPMK - SWL	**0.47**	**0.09**	**-5.07**	**< .001**	**.21**	**-0.43**	**0.13**	**-3.29**	**.002**	**.08**
	PAIRS - GPA	-0.05	0.07	-0.70	.55	-.002	-0.05	0.07	-0.72	.55	.004
	PAIRS - Life Sat.	**0.13**	**0.05**	**2.53**	**.02**	**.02**	**0.14**	**0.06**	**2.38**	**.03**	**.02**
Central Node	DDIP - Rel. Diss	0.53	0.27	1.96	.22	.08	0.33	0.17	1.98	.22	.11
(Individual)	DDIP - Rel. Sat.	0.01	0.14	0.04	.97	-.01	-0.05	0.12	-0.40	.73	.002
	DKPK - BDI	-0.05	0.14	-0.40	.73	-0.02	-0.12	0.12	-0.94	.62	.01
	DKPK - CESD	-0.11	0.13	-0.81	.68	-.01	-0.13	0.11	-1.17	.54	.01
	DKPK - SWL	0.30	0.13	2.19	.22	.06	**0.33**	**0.11**	**0.50**	**.03**	**.10**
	KPMK - CESD	0.06	0.11	0.50	.73	-.01	0.08	0.13	0.59	.54	.01
	KPMK - SWL	0.09	0.12	0.70	.62	-0.01	0.17	0.12	1.40	.42	.02
	PAIRS - GPA	-0.11	0.08	-1.41	.42	.01	-0.12	0.08	-1.50	.42	.01
	PAIRS - Life Sat.	-0.04	0.07	-1.09	.68	.04	-0.07	0.07	-1.09	.55	.01
Sum Score	DDIP - Rel. Diss	-0.32	0.15	-2.10	.08	.03	-0.32	0.17	-1.97	.10	.08
	DDIP - Rel. Sat.	**0.25**	**0.07**	**3.54**	**.002**	**.06**	**0.24**	**0.09**	**2.65**	**.02**	**.20**
	DKPK - BDI	0.13	0.10	1.30	.26	.01	**0.27**	**0.10**	**2.65**	**.02**	**.06**
	DKPK - CESD	0.13	0.10	1.29	.26	.01	**0.32**	**0.09**	**3.47**	**.002**	**.08**
	DKPK - SWL	-0.08	0.10	-0.79	.47	-.003	**-0.30**	**0.10**	**-3.00**	**.01**	**.07**
	KPMK - CESD	**0.40**	**0.10**	**4.21**	**< .001**	**.15**	0.10	0.13	0.77	.47	.004
	KPMK - SWL	**-0.40**	**0.10**	**-4.19**	**< .001**	**.15**	-0.17	0.14	-1.29	.26	.01
	PAIRS - GPA	-0.07	0.07	-1.09	.33	.001	-0.05	0.08	-0.61	.54	.001
	PAIRS - Life Sat.	0.08	0.05	1.55	.22	.004	0.08	0.06	1.37	.26	.01

Note. Bolded lines represent effects that are significant after a false discovery rate adjustment. Rel. Diss. = Relationship Dissolution, Rel. Sat. = Relationship Satisfaction, CESD = Center for Epidemiologic Studies Depression Scale, BDI = Beck Depression Inventory, SWL = Satisfaction with Life Scale, Life Sat. = Life Satisafaction, Modularity = Maximum modularity coefficient, Network strength = global network out-strength. R^2 for multiple regression analyses is the squared semi-partial correlation.

4. DISCUSSION

After representing a psychological construct as a network model, there is no consensus on how to best model this construct in the context of a larger model, as either the predictor or the outcome of other relevant variables. In addition, most research that has attempted to answer this question has fit a single network to a single group of participants, limiting how the network can be summarized and used for prediction. To investigate whether properties of individual networks can be useful for prediction, we fit person-specific networks to four intensive longitudinal datasets across three research areas and evaluated the predictive utility of six network-informed and network structure variables.

In line with previous research, we found that networks can be informative about the best predictor variable: the node with the highest out-strength centrality across all participants successfully predicted seven out of the nine outcomes we assessed. Most of these successful predictions arose when the networks represented positive and negative affect, and six out of these seven remained significant when controlling for all other metrics as additional predictors.

The second most consistent predictor of the outcomes we assessed was the average sum score, which is not informed by any properties of the estimated network. Sum scores successfully predicted depression and life satisfaction in the KPMK dataset, and relationship satisfaction in the DDIP dataset. This predictor remained significant after controlling for all other features only in the DDIP dataset, but also became a significant predictor of depression and life satisfaction in the DKPK dataset.

These findings align with previous work, such as Levinson et al. (2021), that has found variables with highest node centrality to be related to outcomes of interest. Given that the node with the strongest out-strength is expected to have the greatest influence in the network, it is perhaps not surprising that the average value of this node would be related to our outcomes. Furthermore, the average value of the most central node remained a significant predictor even after controlling for the average sum score (which includes the most central node in its calculation), indicating that the value of the central node contained some predictive ability above and beyond the values of all the nodes in the network. The use of out-strength centrality in this paper was motivated by the fact that (1) it is a better measure of how much direct impact a node has in a network, compared to other common measures such as betweenness or closeness centrality, (2) it is considered to be more stable than other centrality measures, and (3) it is commonly reported and interpreted in empirical research. We note, however, that other centrality measures such as betweenness, closeness, and controllability centrality could also be used to identify the most central node (Bringmann et al., 2019; Henry et al., 2022) [3]. Although different centrality measures may choose different nodes as the most influential, and the value of these nodes may differ in how well they can predict psychological outcomes, these differences in

[3] We repeated our analyses using controllability centrality to determine the most central node instead of out-strength centrality. The results from these analyses are available on the OSF page, and they echo the results already presented in this paper

performance can be due to how well a given centrality index is able to choose the most influential node. However, this does not detract from the main finding of our paper: choosing a node based on some centrality index, and then relating the value of that node to an outcome, is one way to relate psychometric networks to other psychological variables, and this approach performed consistently well across our four datasets. Researchers interested in using this approach in their own research can choose different centrality measures than those used in this paper, based on what is the most appropriate for their research question.

Some of the measures considered here, such as density, have been related to variables outside the network in previous work, so their lack of association in this work could be due to the research areas studied here. For example, most research that has found network density to be an important predictor (Borkulo et al., 2015; Lee et al., 2023; Pe et al., 2015) has done so in symptom networks of major depressive disorder, where greater density is considered to represent greater vulnerability or susceptibility to the disorder. Along similar lines, although the average sum score was occasionally related to some of our outcomes, its interpretation is much more difficult in the research contexts we studied here. While the sum score of psychopathological symptoms can represent a disorder's level of severity, it is harder to determine what the sum of positive and negative affect items, or the sum of personality items of different traits, represents. In future explorations, it would be more meaningful to split these characteristics by item valence or facet.

4.1 Limitations and Future Directions

The biggest caveat of our results lies in the network estimation. The longest possible time series amongst our datasets was 98 timepoints, although most participants provided fewer due to missingness. Previous research by Mansueto et al. (2022) indicates that temporal networks estimated on data with 100 timepoints or fewer, as is the case here, have low ability to estimate truly non-zero edges. On the other hand, work by Zhang (2024) indicates that the risk of overfitting in temporal networks (estimating too many connections) is higher when fewer than 100 timepoints are used. The low number of timepoints might explain why the vast majority of estimated temporal networks were either fully saturated or empty, especially as the number of nodes involved increased, as can be seen in Figure 2. This meant that some of the network characteristics studied here—such as density, network strength, and the value of each individual's most central node—either could not be estimated for all individuals, or would have little to no variability across participants. This lack of information and variability might explain why these characteristics failed to predict our outcomes. As such, our results do not indicate that network structure variables cannot be useful for prediction, but they may suggest that longer time series are needed to estimate temporal networks (and the resulting network structure variables) accurately.

A second limitation of this research is that our determination of which network characteristics were

considered predictive is based solely on p-value significance, both when entered into a simple regression model and after controlling for other network characteristics in a multiple regression model. However, even when the network characteristic was a significant predictor, the squared semi-partial correlations were similar, indicating a relatively similar amount of unique variance explained by all network features.

A third limitation of the current study is that none of our datasets assessed psychopathological symptoms, despite many applications of psychometric networks being in the clinical field. Therefore, an important future direction would be to reproduce these results in a clinical dataset. As mentioned in the discussion above, it is possible that the lack of associations between some of the network features studied here and the outcomes in our datasets might be due to the specific research areas we examined. It is possible that such associations are more likely to appear between symptom networks and clinical outcomes, given that some of the network-structure variables have greater interpretability in that context.

Finally, the network features used in this paper are by no means an exhaustive list of how psychometric networks can be summarized and related to other constructs. Other possibilities include, for example, directly relating each node's value of out-strength centrality to the outcome of interest [4] (although in our case, this would limit generalizability across the four datasets), or using network scores, which are derived from network loadings in exploratory graph analysis and are analogous to factor scores in factor analytic models (Christensen & Golino, 2021; Golino et al., 2022). However, we believe that the work presented in this paper represents an important beginning to systematically exploring how network models can be embedded in larger structural models.

5. CONCLUSION

This article describes an initial exploration of how constructs instantiated in individual temporal network models can be related to other psychological constructs. We identified five ways to represent the network-instantiated construct which reflected different—and theoretically relevant—aspects of the network model. In the four datasets we used, we found no evidence that network structure variables like network density or modularity were associated with any outcome measures, but network-identified variables, such as the value of the most central node across participants, was frequently related to outcome measures. We draw no strong conclusions from these results, but present them as an initial point of departure for more research in this area.

[4] We explored this approach in these datasets, and predicted each outcome from the value of out-strength centrality. We found no statistically significant relations

6. ACKNOWLEDGEMENTS

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7. CONFLICTS OF INTEREST

The authors report no competing interests.

8. AUTHOR CONTRIBUTIONS

S.K.J. analyzed the data, and S.K.J. and M.R. drafted the manuscript. All authors provided critical revisions.

REFERENCES

- Beck, A., Steer, R. A., & Brown, G. K. (1987). *Beck depression inventory*. Harcourt Brace Jovanovich New York:
- Beck, E. D., & Jackson, J. J. (2017). More than the sum of its parts? using personality networks to predict outcomes.
- Berg, J. W. van den, Smid, W., Kossakowski, J. J., Beek, D. van, Borsboom, D., Janssen, E., & Gijs, L. (2020). The application of network analysis to dynamic risk factors in adult male sex offenders. *Clinical Psychological Science*, *8*(3), 539–554. https://doi.org/10.1177/2167702620901720
- Blanken, T. F., Borsboom, D., Penninx, B. W. J. H., & Van Someren, E. J. W. (2019). Network outcome analysis identifies difficulty initiating sleep as a primary target for prevention of depression. *Sleep*, *42*(12), zsz288. https://doi.org/10.1093/sleep/zsz288
- Borkulo, C. van, Boschloo, L., Borsboom, D., Penninx, B. W., Waldorp, L. J., & Schoevers, R. A. (2015). Association of symptom network structure with the course of longitudinal depression. *JAMA psychiatry*, *72*(12), 1219–1226. https://doi.org/10.1001/jamapsychiatry.2015.2079
- Borkulo, C. D. V., Bork, R. V., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Borsboom, D., & Waldorp, L. J. (2022). Comparing Network Structures on Three Aspects : A Permutation Test. *Psychological Methods*. https://doi.org/10.1037/met0000476
- Borsboom, D., & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, *9*(1), 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608
- Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki, A. C., Borkulo, C. D. van, Bork, R. van, & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, *1*(1). https://doi.org/10.1038/s43586-021-00055-w

- Bos, F. M., Snippe, E., Vos, S. de, Hartmann, J. A., Simons, C. J., Krieke, L. van der, Jonge, P. de, & Wichers, M. (2017). Can we jump from cross-sectional to dynamic interpretations of networks implications for the network perspective in psychiatry. *Psychotherapy and psychosomatics*, *86*(3), 175–177. https://doi.org/10.1159/000453583
- Boschloo, L., Borkulo, C. D. van, Rhemtulla, M., Keyes, K. M., Borsboom, D., & Schoevers, R. A. (2015). The network structure of symptoms of the diagnostic and statistical manual of mental disorders. *PloS one*, *10*(9), e0137621. https://doi.org/10.1371/journal.pone.0137621
- Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T., & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of abnormal psychology*, *128*(8), 892. https://doi.org/10.1037/abn0000446
- Brown, T. A., Vanzhula, I. A., Reilly, E. E., Levinson, C. A., Berner, L. A., Krueger, A., Lavender, J. M., Kaye, W. H., & Wierenga, C. E. (2020). Body mistrust bridges interoceptive awareness and eating disorder symptoms. *Journal of Abnormal Psychology*, *129*(5), 445. https://doi.org/10.1037/abn0000516
- Christensen, A. P., & Golino, H. (2021). On the equivalency of factor and network loadings. *Behavior research methods*, *53*(4), 1563–1580. https://doi.org/10.3758/s13428-020-01500-6
- Christensen, A. P., & Kenett, Y. N. (2021). Semantic network analysis (semna): A tutorial on preprocessing, estimating, and analyzing semantic networks. *Psychological Methods*, *28*(4). https://doi.org/10.1037/met0000463
- Costantini, G., Richetin, J., Preti, E., Casini, E., Epskamp, S., & Perugini, M. (2019). Stability and variability of personality networks. a tutorial on recent developments in network psychometrics. *Personality and Individual Differences*, *136*, 68–78. https://doi.org/10.1016/j.paid.2017.06.011
- Cramer, A. O., Van Borkulo, C. D., Giltay, E. J., Van Der Maas, H. L., Kendler, K. S., Scheffer, M., & Borsboom, D. (2016). Major depression as a complex dynamic system. *PloS one*, *11*(12), e0167490. https://doi.org/10.1371/journal.pone.0167490
- Dalege, J., Borsboom, D., Van Harreveld, F., Waldorp, L. J., & Van Der Maas, H. L. (2017). Network Structure Explains the Impact of Attitudes on Voting Decisions. *Scientific Reports*, *7*(1), 1–11. https://doi.org/10.1038/s41598-017-05048-y
- Dejonckheere, E., Kalokerinos, E. K., Bastian, B., & Kuppens, P. (2019). Poor emotion regulation ability mediates the link between depressive symptoms and affective bipolarity. *Cognition and Emotion*, *33*(5), 1076–1083. https://doi.org/10.1080/02699931.2018.1524747
- Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of personality assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13
- Ding, F., Li, N., Zhang, S., Li, J., Jing, Z., & Zhao, Y. (2023). Network comparison analysis of comorbid depression and anxiety disorder in a large clinical sample before and after treatment. *Current Psychology*, 1–12. https://doi.org/10.1007/s12144-023-05308-3
- Elliott, H., Jones, P. J., & Schmidt, U. (2020). Central symptoms predict posttreatment outcomes and clinical impairment in anorexia ner-

vosa: A network analysis. *Clinical Psychological Science*, *8*(1), 139–154. https://doi.org/10.1177/2167702619865958

- Epskamp, S. (2023). *Psychonetrics: Structural equation modeling and confirmatory network analysis*. https://CRAN.R-project.org/package=psychonetrics
- Epskamp, S., Borsboom, D., & Fried, E. I. (2018a). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior research methods*, *50*, 195–212. https://doi.org/10.3758/s13428-017-0862-1
- Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04
- Epskamp, S., & Fried, E. I. (2018). A Tutorial on Regularized Partial Correlation Networks. *Psychological Methods*, *23*(4), 617–634. https://doi.org/10.1037/met0000167
- Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018b). The gaussian graphical model in cross-sectional and time-series data. *Multivariate behavioral research*, *53*(4), 453–480. https://doi.org/10.1080/00273171.2018.1454823
- Ferguson, C., & Initiative, A. D. N. (2021). A network psychometric approach to neurocognition in early alzheimer's disease. *Cortex*, *137*, 61–73. https://doi.org/10.1016/j.cortex.2021.01.002
- Ferrer, E., Steele, J. S., & Hsieh, F. (2012). Analyzing the dynamics of affective dyadic interactions using patterns of intra-and interindividual variability. *Multivariate Behavioral Research*, *47*(1), 136–171. https://doi.org/10.1080/00273171.2012.640605
- Fletcher, G. J., Simpson, J. A., & Thomas, G. (2000). Ideals, perceptions, and evaluations in early relationship development. *Journal of personality and social psychology*, *79*(6), 933. https://doi.org/10.1037/0022-3514.79.6.933
- Fortunato, S. (2010). Community detection in graphs. *Physics reports*, *486*(3-5), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002
- Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., Dijk, H. M. Huisman-van, Bockting, C. L., Engelhard, I., Armour, C., Nielsen, A. B., & Karstoft, K.-I. (2018). Replicability and generalizability of posttraumatic stress disorder (ptsd) networks: A cross-cultural multisite study of ptsd symptoms in four trauma patient samples. *Clinical Psychological Science*, *6*(3), 335–351. https://doi.org/10.1177/2167702617745092
- Fried, E. I., Epskamp, S., Nesse, R. M., Tuerlinckx, F., & Borsboom, D. (2016). What are' good' depression symptoms? comparing the centrality of dsm and non-dsm symptoms of depression in a network analysis. *Journal of affective disorders*, *189*, 314–320. https://doi.org/10.1016/j.jad.2015.09.005
- Golino, H., & Christensen, A. P. (2023). *Eganet: Exploratory graph analysis – a framework for estimating the number of dimensions in multivariate data using network psychometrics*. https://r-ega.net
- Golino, H., Christensen, A. P., Moulder, R., Kim, S., & Boker, S. M. (2022). Modeling latent topics in social media using dynamic exploratory graph analysis: The case of the right-wing and left-wing trolls in the 2016 us elections. *Psy-

chometrika, 1–32. https://doi.org/10.1007/s11336-021-09820-y

- Golino, H., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PloS one*, *12*(6), e0174035. https://doi.org/10.1371/journal.pone.0174035
- Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martinez-Molina, A. (2020). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, *25*(3), 292. https://doi.org/10.1037/met0000255
- Haag, C., Robinaugh, D. J., Ehlers, A., & Kleim, B. (2017). Understanding the emergence of chronic posttraumatic stress disorder through acute stress symptom networks. *JAMA psychiatry*, *74*(6), 649–650. https://doi.org/10.1001/jamapsychiatry.2017.0788
- Hagan, K. E., Matheson, B. E., Datta, N., L'Insalata, A. M., Onipede, Z. A., Gorrell, S., Mondal, S., Bohon, C. M., Le Grange, D., & Lock, J. D. (2023). Understanding outcomes in family-based treatment for adolescent anorexia nervosa: A network approach. *Psychological Medicine*, *53*(2), 396–407. https://doi.org/10.1017/S0033291721001604
- Henry, T. R., Robinaugh, D. J., & Fried, E. I. (2022). On the control of psychological networks. *Psychometrika*, *87*(1), 188–213. https://doi.org/10.1007/s11336-021-09796-9
- John, O. P. (1991). The big five inventory—versions 4a and 54. *(No Title)*.
- Kenett, Y. N., Gold, R., & Faust, M. (2016). The hyper-modular associative mind: A computational analysis of associative responses of persons with asperger syndrome. *Language and Speech*, *59*(3), 297–317.
- Klipstein, L. von, Riese, H., Veen, D. C. van der, Servaas, M. N., & Schoevers, R. A. (2020). Using person-specific networks in psychotherapy: challenges, limitations, and how we could use them anyway. *BMC Medicine*, *18*(345). https://doi.org/10.1186/s12916-020-01818-0
- Koval, P., Pe, M. L., Meers, K., & Kuppens, P. (2013). Affect dynamics in relation to depressive symptoms: Variable, unstable or inert? *Emotion*, *13*(6), 1132. https://doi.org/10.1037/a0033579
- Lee, C. T., Kelley, S. W., Palacios, J., Richards, D., & Gillan, C. M. (2023). Estimating the prognostic value of cross-sectional network connectivity for treatment response in depression. *Psychological Medicine*, 1–10. https://doi.org/10.1017/S0033291723001368
- Levinson, C. A., Hunt, R. A., Christian, C., Williams, B. M., Keshishian, A. C., Vanzhula, I. A., & Ralph-Nearman, C. (2021). Longitudinal group and individual networks of eating disorder symptoms in individuals diagnosed with an eating disorder. *Journal of Abnormal Psychology*, *131*(1), 58–72. https://doi.org/10.1037/abn0000727
- Levinson, C. A., & Williams, B. M. (2020). Eating disorder fear networks: Identification of central eating disorder fears. *International Journal of Eating Disorders*, *53*(12), 1960–1973. https://doi.org/10.1002/eat.23382
- Lunansky, G., Naberman, J., Borkulo, C. D. van, Chen, C., Wang, L., & Borsboom, D. (2022). Intervening on psychopathology networks: Evaluating intervention targets through simulations.

Methods, *204*, 29–37. https://doi.org/10.1016/j.ymeth.2021.11.006

- Mansueto, A. C., Wiers, R. W., Weert, J. van, Schouten, B. C., & Epskamp, S. (2022). Investigating the feasibility of idiographic network models. *Psychological methods*. https://doi.org/10.1037/met0000466
- Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the national academy of sciences*, *103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103
- Nissen, A. T., & Beck, E. D. (2024). Linking person-specific network parameters to between-person change. *PsyArXiv*. https://doi.org/10.31234/osf.io/pvubn
- Olatunji, B. O., Christian, C., Brosof, L., Tolin, D. F., & Levinson, C. A. (2019). What is at the core of ocd? a network analysis of selected obsessive-compulsive symptoms and beliefs. *Journal of Affective Disorders*, *257*, 45–54. https://doi.org/10.1016/j.jad.2019.06.064
- Olatunji, B. O., Levinson, C., & Calebs, B. (2018). A network analysis of eating disorder symptoms and characteristics in an inpatient sample. *Psychiatry research*, *262*, 270–281. https://doi.org/10.1016/j.psychres.2018.02.027
- Papini, S., Rubin, M., Telch, M. J., Smits, J. A. J., & Hien, D. A. (2020). Pretreatment posttraumatic stress disorder symptom network metrics predict the strength of the association between node change and network change during treatment. *Journal of Traumatic Stress*, *33*(1), 64–71. https://doi.org/10.1002/jts.22379
- Pe, M. L., Kircanski, K., Thompson, R. J., Bringmann, L. F., Tuerlinckx, F., Mestdagh, M., Mata, J., Jaeggi, S. M., Buschkuehl, M., Jonides, J., Kuppens, P., & Gotlib, I. H. (2015). Emotion-network density in major depressive disorder. *Clinical Psychological Science*, *3*(2), 292–300. https://doi.org/10.1177/2167702614540645
- Radloff, L. S. (1977). The ces-d scale: A self-report depression scale for research in the general population. *Applied psychological measurement*, *1*(3), 385–401. https://doi.org/10.1177/014662167700100306
- Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of abnormal psychology*, *125*(6), 747. https://doi.org/10.1037/abn0000181
- Rodebaugh, T. L., Tonge, N. A., Piccirillo, M. L., Fried, E., Horenstein, A., Morrison, A. S., Goldin, P., Gross, J. J., Lim, M. H., Fernandez, K. C., Blanco, C., Schneier, F. R., Bogdan, R., Thompson, R. J., & Heimberg, R. G. (2018). Does centrality in a cross-sectional network suggest intervention targets for social anxiety disorder? *Journal of consulting and clinical psychology*, *86*(10), 831. https://doi.org/10.1037/ccp0000336
- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02
- Ryan, O., Bringmann, L. F., & Schuurman, N. K. (2022). The challenge of generating causal hypotheses using network models. *Structural Equation Modeling: A Multidisciplinary Journal*, *29*(6), 953–970. https://doi.org/10.1080/10705511.2022.2056039
- Schueler, K., Fritz, J., Dorfschmidt, L., Van Harmelen, A.-L., Stroemer, E., & Wessa, M. (2021). Psychological network analysis of general self-efficacy in high vs. low resilient functioning healthy adults. *Frontiers in psychiatry*,

12, 736147. https://doi.org/10.3389/fpsyt.2021.736147

- Schweren, L., Van Borkulo, C. D., Fried, E., & Goodyer, I. M. (2018). Assessment of symptom network density as a prognostic marker of treatment response in adolescent depression. *JAMA psychiatry*, *75*(1), 98–100. https://doi.org/10.1001/jamapsychiatry.2017.3561
- Siew, C. S. (2013). Community structure in the phonological network. *Frontiers in psychology*, *4*, 553. https://doi.org/10.3389/fpsyg.2013.00553
- Siew, C. S., McCartney, M. J., & Vitevitch, M. S. (2019). Using network science to understand statistics anxiety among college students. *Scholarship of Teaching and Learning in Psychology*, *5*(1), 75. https://doi.org/10.1037/stl0000133
- Smith, K. E., Mason, T. B., Crosby, R. D., Cao, L., Leonard, R. C., Wetterneck, C. T., Smith, B. E., Farrell, N. R., Riemann, B. C., Wonderlich, S. A., & Moessner, M. (2019). A comparative network analysis of eating disorder psychopathology and co-occurring depression and anxiety symptoms before and after treatment. *Psychological Medicine*, *49*(2), 314–324. https://doi.org/10.1017/S0033291718000867
- Spiller, T. R., Levi, O., Neria, Y., Suarez-Jimenez, B., Bar-Haim, Y., & Lazarov, A. (2020). On the validity of the centrality hypothesis in cross-sectional between-subject networks of psychopathology. *BMC medicine*, *18*(1), 1–14. https://doi.org/10.1186/s12916-020-01740-5
- Stella, M. (2022). Network psychometrics and cognitive network science open new ways for understanding math anxiety as a complex system. *Journal of Complex Networks*, *10*(3), cnac012. https://doi.org/10.1093/comnet/cnac012
- Sweet, T. M. (2019). Modeling Social Networks as Mediators: A Mixed Membership Stochastic Blockmodel for Mediation. *Journal of Educational and Behavioral Statistics*, *44*(2), 210–240. https://doi.org/10.3102/1076998618814255
- Sweet, T. M., & Zheng, Q. (2018). Estimating the effects of network covariates on subgroup insularity with a hierarchical mixed membership stochastic blockmodel. *Social Networks*, *52*, 100–114. https://doi.org/10.1016/j.socnet.2017.05.008
- Van Der Maas, H. L., Kan, K.-J., Marsman, M., & Stevenson, C. E. (2017). Network models for cognitive development and intelligence. *Journal of Intelligence*, *5*(2), 16. https://doi.org/10.3390/jintelligence5020016
- Vazire, S., Wilson, R. E., Solomon, B., Bollich, K., Harris, K., Weston, S., & Jackson, J. J. (2015). Personality and interpersonal roles (pairs).
- Williams, D. R., & Rast, P. (2020). Back to the basics: Rethinking partial correlation network methodology. *British Journal of Mathematical and Statistical Psychology*, *73*(2), 187–212. https://doi.org/10.1111/bmsp.12173
- Williams, D. R., Rhemtulla, M., Wysocki, A. C., & Rast, P. (2019). On nonregularized estimation of psychological networks. *Multivariate Behavioral Research*, *54*(5), 719–750. https://doi.org/10.1080/00273171.2019.1575716
- Wysocki, A. C., Lawson, K. M., & Rhemtulla, M. (2022). Statistical control requires causal justification. *Advances in Methods and Practices in Psychological Science*, *5*(2), 25152459221095823. https://doi.org/10.1177/25152459221095823

- Zhang, Y. (2024). *Sample size optimization for idiographic temporal networks using predictive accuracy analysis* [Association for Psychological Science. San Francisco, CA].
- Zhou, J., Liu, S., Mayes, T. L., Feng, Y., Fang, M., Xiao, L., & Wang, G. (2022). The network analysis of depressive symptoms before and after two weeks of antidepressant treatment. *Journal of Affective Disorders*, *299*, 126–134. https://doi.org/10.1016/j.jad.2021.11.059

A. APPENDIX

Table 5
Correlation Matrices for Network-Derived Metrics and Sum Score

	DKPK					
	Density	Modularity	Freq. Central Node	Ind. Central Node	Network Strength	Sum Score
Density	1					
Modularity	.05	1				
Freq. Central Node	.00	-.01	1			
Ind. Central Node	-.04	-.16	.16	1		
Network Strength	.44	.12	.12	-.13	1	
Sum Score	-.17	-.21	.26	.26	-.03	1

	KPMK					
	Density	Modularity	Freq. Central Node	Ind. Central Node	Network Strength	Sum Score
Density	1					
Modularity	.03	1				
Freq. Central Node	-.36	-.18	1			
Ind. Central Node	.36	.12	.06	1		
Network Strength	.45	-.03	-.10	.16	1	
Sum Score	-.41	-.17	.74	-.03	-.09	1

	PAIRS					
	Density	Modularity	Freq. Central Node	Ind. Central Node	Network Strength	Sum Score
Density	1					
Modularity	-.02	1				
Freq. Central Node	-.12	.03	1			
Ind. Central Node	-.08	.09	.14	1		
Network Strength	-.07	.06	.00	-.08	1	
Sum Score	.00	.01	.23	.29	-.07	1

	DDIP					
	Density	Modularity	Freq. Central Node	Ind. Central Node	Network Strength	Sum Score
Density	1					
Modularity[a]	-	1				
Freq. Central Node	-.25	-.08	1			
Ind. Central Node	-.18	-.08	.25	1		
Network Strength	.67	-.05	-.12	-.17	1	
Sum Score	-.20	-.06	.52	.18	-.07	1

Modularity = Maximum modularity coefficient, Network strength = Global network out-strength, Freq. Central Node = Average value of most frequently central node, Ind. Central Node = Average value of individual's most central node

[a] Density and modularity are uncorrelated due to lack of variance in density values